

# FOCUSING OF OPINIONS IN THE DEFFUANT MODEL: FIRST IMPRESSION COUNTS

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The paper treats opinion dynamics of an unequal distribution as the initial opinion distribution. Simulated is the Deffuant model on a directed Barabási-Albert network with discrete opinions and several subjects. Noticed is a focusing of the the resulting opinion distribution during the simulation towards the average value of the initial opinion distribution. A small change of the focusing is seen. A dependency of this change on the number of subjects and opinions is detected and indicates the change as a consequence of discretization the opinions. Hereby the average value of the initial opinion distribution can be identified as the guide of opinion forming.

*Keywords:* Opinion Dynamics; Deffuant-Model; Sociophysics; Monte-Carlo Simulation

## 1. Introduction

The human brain is an economically working organ. It received a lot of informations from 'outside' (senses) and 'inside' (memories, associations). Not to be paralysed by working up all informations at the same time, it follows a strategy of stepwise refinement. At the beginning it forms a first impression, which integrates more or less all informations. It goes on in controlling and weighting all relevant informations and summarises them. At the end stands a conclusion<sup>1</sup>.

People watching a movie or a performance, meeting another person, regarding something new, etc., do the same working method for evaluation as the brain does. At the beginning stands a first impression. After leaving the theater and discussing the movie or performance, having a talk with a new acquaintance, examining the news more closely, they form in the end, starting from the first impression, by checking in detail, a personal opinion.

Someone can take the first impression as the first truth. In discussing, talking or examining, this first truth will be the guide (canon) of opinion forming. This way of giving an opinion on truth weight, has been done by Assmann<sup>2</sup>, Krause and Hegselmann<sup>3</sup>, and Malarz<sup>4</sup>.

The Deffuant model offers a choice for reproducing this process. Therefore, supposing that the impressions of all humans are similar<sup>5</sup>, I choose a value as the average of all opinions of all agents. I set this value as the first impression.

Therefore at the beginning of the simulation is a arrangement of opinions, which gives on average the chosen value of impression.

## 2. Model

The model simulates a consensus forming process. The agents are connected via a directed Barabási-Albert network<sup>6</sup>. The opinion exchange follows Deffuant et al.<sup>7</sup> with discrete opinions and several subjects (= questions, themes, ...).

Every agent  $i$  ( $i = 1, 2, \dots, N$ ) has on each subject  $S_k$  ( $k = 1, 2, \dots, S$ ) an opinion  $O_i^k$ . The discrete opinion spectrum comprises natural numbers from 1 to  $O$ .

Simulations of a consensus model á la Deffuant on a directed Barabási-Albert network with discrete opinions have been made with one subject in<sup>9</sup>, with several subjects in<sup>10,11</sup>.

### 2.1. Network assembly

At the beginning one knot of  $m + 1$  agents, each connected with all others, is built. Every newly added agent  $i$  connects itself with  $m$  already existing agents in the network. The connection takes place stochastically. With it the probability of connecting with an already existing agent is proportional to the total number of the connections of this pre-existing agent ("The rich get richer").

Besides the connection is directed, i.e., the agents search a partner along the  $m$  connections, which they connect. The connections, with whom they connected later when new agents are added, can not be chosen by themselves.

### 2.2. Communication

The communication takes place along the connections. The agents become the active communicator  $i$  in the order they have been bound into the network. The partner for communication  $j$  will be chosen randomly from the  $m$  with those to whom  $i$  has connected itself. Then the over-all distance  $\delta$  to the partner of communication will be calculated. This  $\delta$  results from the absolute value of the distance of the opinions on all subjects to each other

$$\delta = \sum_{k=1}^S |O_i^k - O_j^k|, \quad (1)$$

and is the indicator for the start of a communication: If  $\delta$  is lower or equal a given  $\Delta = (O - 1) S \varepsilon$  then a communication will start ( $\varepsilon$  with  $0 < \varepsilon < 1$  is an input parameter). Otherwise it is the next agents' turn.

#### 2.2.1. Rules for Simulating the Communication:

Now agents  $i$  and  $j$  look randomly for a subject  $S_k$  on which they will communicate.

- If the difference of opinions ( $O_i^k - O_j^k$ ) of both partners of communication on the subject  $k$  results in zero, then they agree and the communication ends.
- If the difference of opinions equals one, one communicant will adopt randomly the opinion from the other.

- If the difference of opinions is larger than one, both communicants approach each other by the amount  $d$ , with rounding the opinion.

With  $d = \sqrt{1/10} (O_i^k - O_j^k)$ , it will be  $O_i^k := O_i^k - d$  and  $O_j^k := O_j^k + d$ .

After that it is the next agents' turn.

The simulation ends, when during  $n$  iterations over all agents no change of opinion in one of the communications takes place.

### 2.3. First Impression

'First Impression' is the initial mean opinion of all the networks agents opinions in all subjects  $S$ . The equal distribution has the median value of the opinion-spectra  $O$ . To realise another than the median value of the opinion-spectra  $O$  means to start with an unequal distribution of the opinions.

This has been done by asynchronous allocation and random displacement of several opinions.

In a second way, I choose for initializing the opinions distribution only two possible opinions. With a probability of 50 % an agent gets for all its subjects one of these two opinions. This way I call a symmetric distribution. I have done simulations with 17 different average network opinions generated by symmetric distributions.

### 2.4. Parameter

The parameters of the model, which have been modified, are:  $\varepsilon$ : tolerance,  $\Delta = (O - 1) S \varepsilon$ ,  $0 \leq \varepsilon \leq 1$ ;  $N$ : Number of agents ( $N$ );  $S$ : Number of subjects ( $S$ );  $O$ : Number of opinions per subject ( $O$ ),  $n$ : stop criterion; the simulation stops if during  $n$  consecutive iterations over all agents no opinion was changed.

The parameter of the model, which has been held constant, is  $m$ : Number of network neighbours ( $m=3$ ).

### 2.5. Methods of Evaluation

#### a) Average Opinion $AO$

The average opinion  $AO$  specifies the mean of all opinions of all agents of the network considering all their subjects.

$$AO = \frac{1}{(S N)} \sum_{i=1}^N \sum_{k=1}^S O_i^k \quad (2)$$

The average opinion at the start of the simulation I call  $AO_{start}$ , at the end of the simulation  $AO_{end}$ .

#### b) Percentage Change $PA$

Before the start of the simulation, I verify the  $AO_{start}$  of the network. After the stop of the simulation I calculate  $AO_{end}$ . The difference of  $AO_{start}$  to

$AO_{end}$  is given in percentage of  $AO_{end}$ :

$$PA = 100 \left( 1 - \frac{AO_{start}}{AO_{end}} \right) \quad (3)$$

A positive sign implies, that the  $AO_{end}$  is larger than  $AO_{start}$ , a negative sign implies the reverse.

c) **Standard Deviation**

From the  $PA$  I calculate an average change  $\overline{PA}$  of all simulations with different average opinions at start.

Also a standard deviation of the percentage change has been calculated. With  $iter =$  the number of simulations:

$$\sigma = \sqrt{\left( \frac{1}{iter - 1} \right) \sum_{i=1}^{iter} (PA_i - \overline{PA})^2} \quad (4)$$

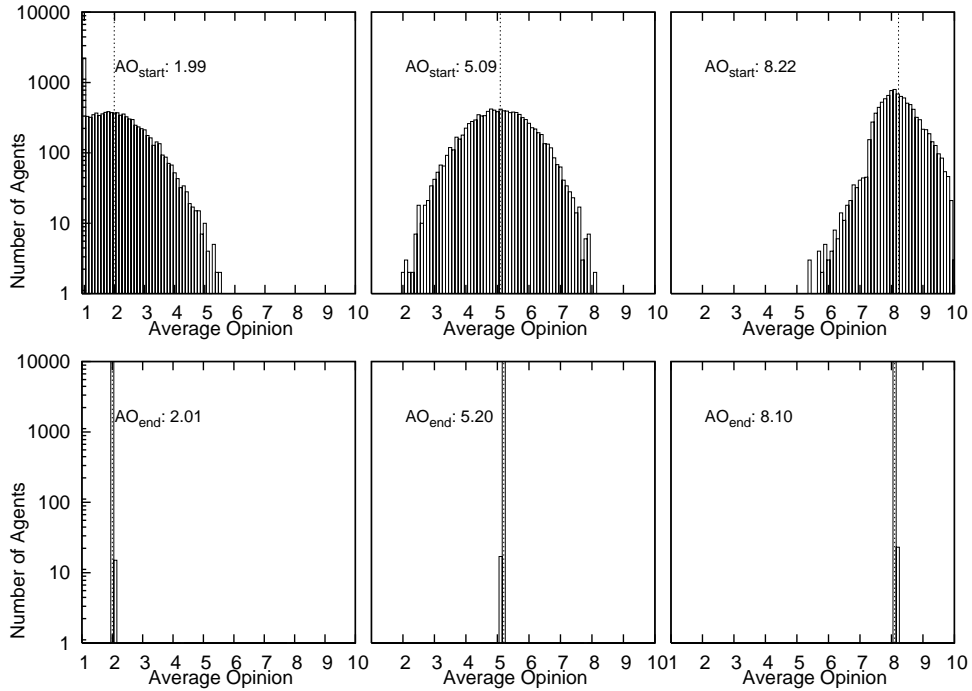


Fig. 1. Unequal opinion distribution: Plotted are the average opinion of the agents. Shown are also  $AO_{start}$  and  $AO_{end}$ .

The upper three graph show different opinion distributions at the start of the simulation  $AO_{start}$ , the three bottom the final opinion distribution  $AO_{end}$  of the simulation, with  $\varepsilon = 1.0$ . The  $y$ -axis is logarithmic. (With  $N=10003$ ,  $O=10$ ,  $S=10$ ,  $n=1$ )

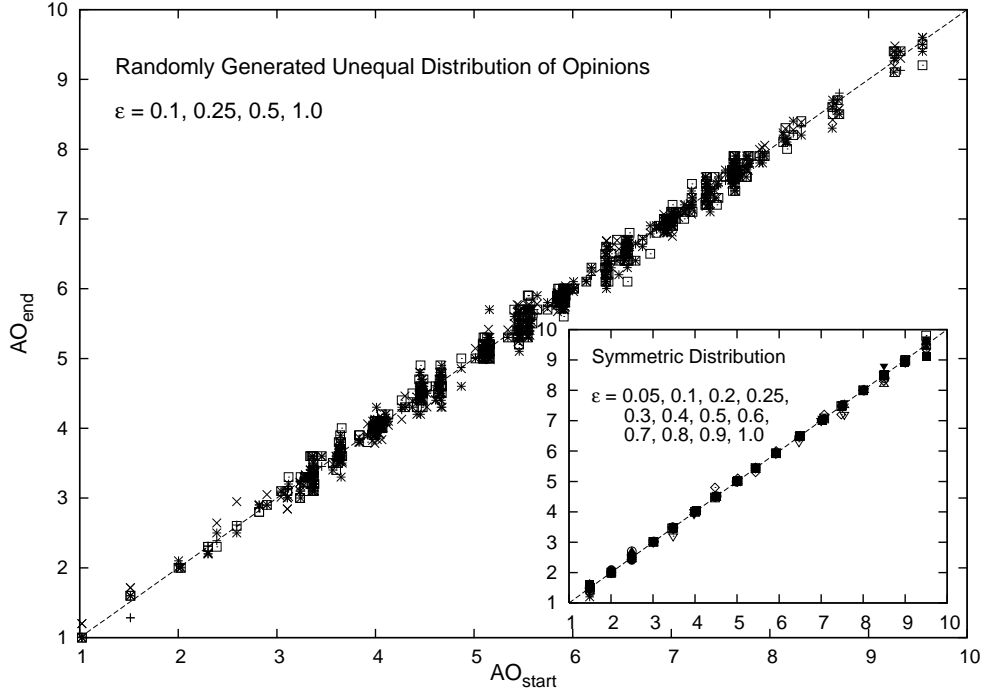


Fig. 2. The  $AO_{start}$  vs.  $AO_{end}$  is plotted. The tendency of  $AO_{start}$  to remain stable is obvious. The  $AO_{end}$  varies in a small interval around the  $AO_{start}$  (with  $N=10003$ ,  $S=10$ ,  $O=10$ ,  $n=1$ ). The graph shows  $AO_{start}$  vs.  $AO_{end}$  of an unequal opinion distribution. In the inset is shown  $AO_{start}$  vs.  $AO_{end}$  of the simulations with the symmetric distribution.

### 3. Simulation

#### 3.1. Description

The simulations have been made with  $\simeq 400$  different non-equal opinions distributions at the start. The  $AO_{end}$  of the simulations has been nearly the same as the  $AO_{start}$  (Fig. 1 and 2).

The general tendency is, that  $AO_{start}$  stays stable, as the initial distribution begin changes. Changing of opinions during an iteration is mostly symmetric (see above, 2.2.1), except the second rule. Therefore with every opinion change the mean opinion between acting agents stays stable, except that an agent adopts randomly the opinion of the other agent <sup>12</sup>.

#### 3.2. Analysis, Standard Deviation

The percentage change  $PA$  has been calculated, as outlined (Eq. 3). The standard deviation (Eq. 4) has been calculated on base of the average percentage change  $\overline{PA}$  of all simulations (Fig. 3 ).

Variations of  $\varepsilon$  do influence the outcome of the simulations.  $\overline{PA}$  stays stable around

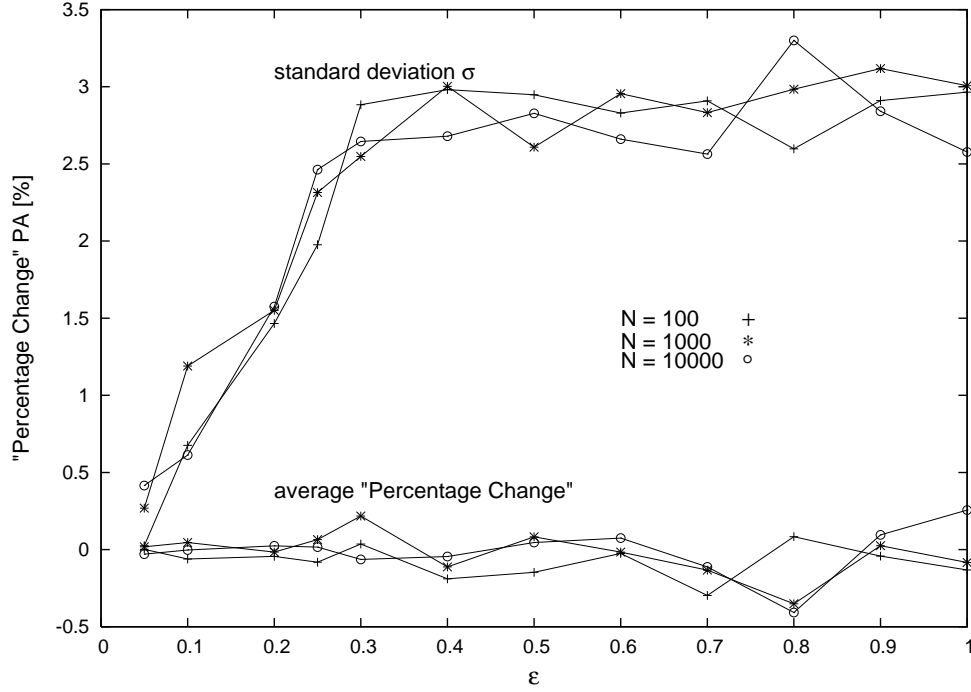


Fig. 3. Comparison of  $\overline{PA}$  vs.  $\epsilon$  (curve on bottom) with the standard deviation  $\sigma$  vs.  $\epsilon$  (curve on top). The simulations have been made with different number of agents  $N$ . No obvious influence of  $N$  on the outcome is visible. (With  $O=10$ ,  $S=10$ ,  $n=1$ )

0, but  $\sigma$  is growing with growing  $\epsilon$  until an  $\epsilon_s$  from there on  $\sigma$  stays stable.  $\epsilon_s$  is identical with the  $\epsilon$  where the minimal number of clusters of the network is reached and nearly all agents share the same opinions in their subjects<sup>10</sup>.

In a simulation with small  $\epsilon$  only a few opinions will be changed, with growing  $\epsilon$  more opinions are changed. The changing are of discrete number, this could explain the uneven curve. The variation of the stop criterion  $n$  and the variation of the number of agents  $N$  (Fig.3) do not obviously influence the outcome of the simulations. But variations of the number of subjects  $S$  (Fig.5) and the opinion spectra  $O$  (Fig.4) affect on the outcome of the simulations.

### 3.2.1. Opinion Spectra

$O$  divided by the smallest steps of modification of the opinions during the simulation gives the number of possible steps changing the opinion. Therefore large  $O$  offers more possible values for  $AO$  than small  $O$ , with it more possible values for  $AO_{end}$  near  $AO_{start}$ . This results in a smaller  $\sigma$  with larger  $O$ .

### 3.2.2. Number of Subjects

An increasing number of  $S$  results in more possible numerical values of the average

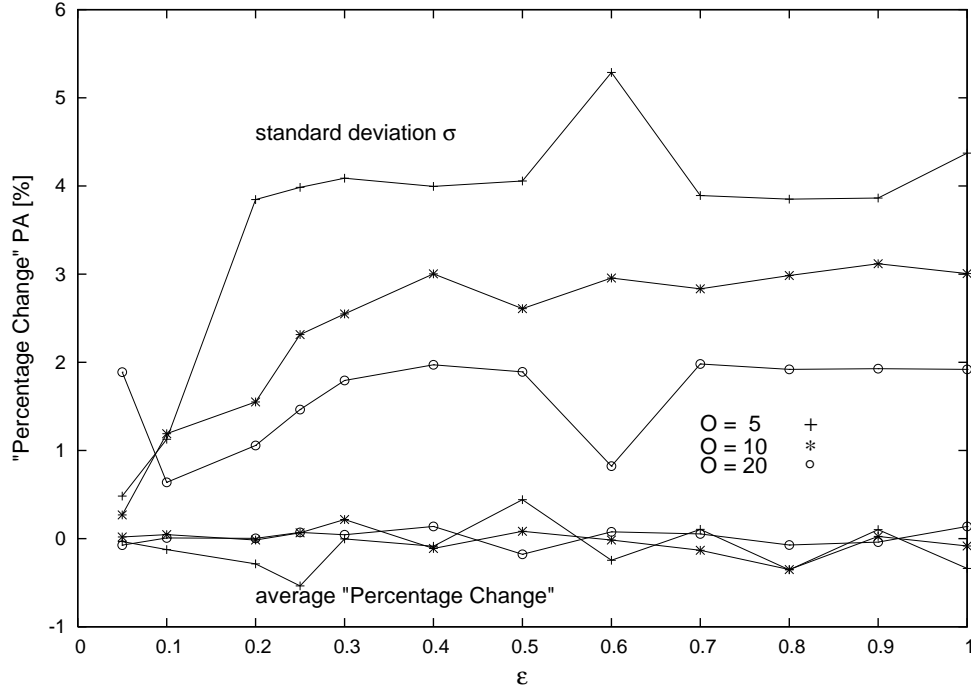


Fig. 4. Comparison of  $\overline{PA}$  vs.  $\epsilon$  (curve on bottom) with the standard deviation  $\sigma$  vs.  $\epsilon$  (curve on top). The simulations have been made with different opinion-spectra  $O$ . Variation of  $O$  affects  $\sigma$ . (With  $N=1003$ ,  $S=10$ ,  $n=1$ )

value and with it in more total values of  $AO$ . Therefore large  $S$  offers more possible values for  $AO_{end}$  than smaller  $S$ . This also results in a smaller  $\sigma$  with larger  $S$ .

#### 4. Conclusion

The Deffuant Algorithm is maintaining the average opinion of the initial opinion distribution. The differences of the  $AO_{start}$  to the  $AO_{end}$  are small<sup>12</sup>. We can presume the origins of this difference in the discretization of opinions. The difference is influenced by  $S$  and  $O$ , due to the discretization.

But the most notably fact is the focus of the algorithm on the mean value of the initial opinion distribution. For a communicative social community means this, that the first impression guides the opinion forming.

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#### References

1. Zimbardo, P.G., Gerrig, R.J, *Psychologie* (Springer-Verlag, Berlin Heidelberg New York, 1999, 7th Ed.), p. 105-114.
2. Assmann, P., *Int. J. Mod. Phys. C*, **15**, 1439 (2004).
3. Hegselmann, R., and Krause, U., *Journal of Artificial Societies and Social Simulation* 9, issue **3**, paper 1 (jasss.soc.surrey.ac.uk) (2006).
4. Malarz, K., e-print arXiv:physics/0607291, to appear in *Int. J. Mod. Phys. C*, **17**, (2006).
5. Winkielman, P., Halberstadt, J., Fazendeiro, T., and Catty, S., *Psychological Science* 17, issue **9**, 799-806 (2006).
6. Barabási, A.-L. and Albert, R., *Science*, **286**, 509 (1999).
7. Deffuant, G., Amblard, F., Weisbuch, G., and Faure, T., *Journal of Artificial Societies and Social Simulation* 5, issue **4**, paper 1 (jasss.soc.surrey.ac.uk) (2002).
8. M. S. Miguel, V. M. Eguíluz, R. Toral, and K. Klemm, *Computing in Science and Engineering*, **12**, 67 (2005).
9. Stauffer, D., Sousa, A. and Schulze, C., *Journal of Artificial Societies and Social Simulation* 7, issue **3**, paper 7 (jasss.soc.surrey.ac.uk) (2004).
10. Jacobmeier, D., *Int. J. Mod. Phys. C*, **16**, 633 (2005).
11. Stauffer, D., Moss de Oliveira, S., de Oliveira, P.M.C., Sá Martins, J.S., *Biology, Sociology, Geology by Computational Physicists* (Elsevier, Amsterdam 2006).
12. Krause, U., talk at *Chaos and Complex Systems* (Novacella, Italy, October 2006).

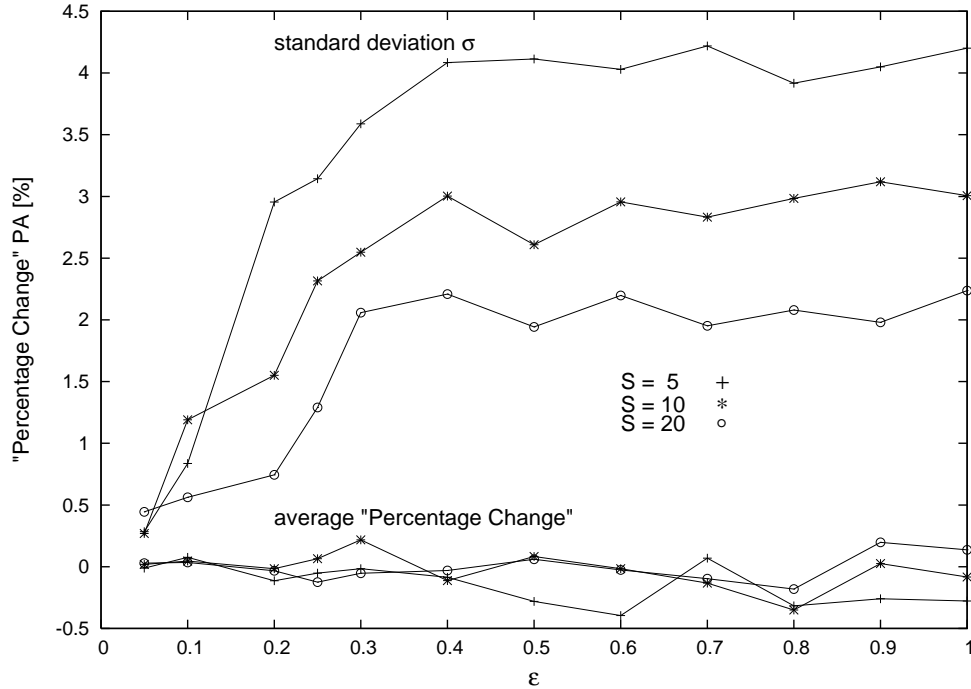


Fig. 5. Comparison of  $\overline{PA}$  vs.  $\varepsilon$  (curve on bottom) with the standard deviation  $\sigma$  vs.  $\varepsilon$  (curve on top). The simulations have been made with different subjects  $S$ . Variation of  $S$  affects  $\sigma$ . (With  $N=1003$ ,  $O=10$ ,  $n=1$ )